Regional Climate Model Biases in the CORDEX-Africa and NARCCAP Hindcast Experiment Data

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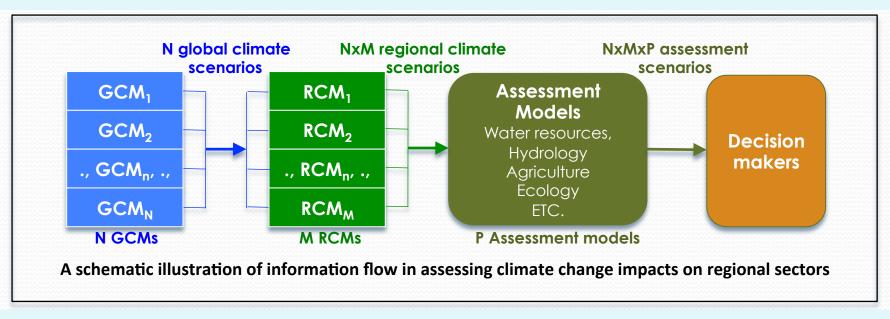
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Related Publications

- Crichton, D.J., C.A. Mattmann, L. Cinquini, A. Braverman, D.E. Waliser, M. Gunson, A. Hart, C. Goodale, P.W. Lean, and J. Kim, 2012: Software and Architecture for Sharing Satellite Observations with the Climate Modeling Community. *IEEE Software*, 29, 63-71.
- Hart, A.F., C.E. Goodale, C.A. Mattmann, P. Zimdars, D. Crichton, P. Lean, Jinwon Kim, and D.E. Waliser, 2011: A cloud-enabled regional climate model evaluation system, ICSE 2011 Workshop Software Engineering for Cloud Computing SECLOUD, Honolulu, HI, May 2011, 43-49, ISBN: 978-1-4503-0582-2, doi: 10.1145/1985500.1985508.
- Kim, Jinwon, D. Waliser, C. Mattmann, C. Goodale, A. Hart, P. Zimdars, D. Crichton, C. Jones, G. Nikulin, B. Hewitson, C. Jack, C. Lennard, and A. Favre, 2013: Evaluation of the CORDEX-Africa multi-RCM hindcast: systematic model errors. Clim Dyn, DOI 10.1007/s00382-013-1751-7.
- Kim, Jinwon, D.E. Waliser, C.A. Mattmann, L.O. Mearns, C.E. Goodale, A.F. Hart, D.J. Crichton, S. McGinnis, H. Lee, P.C. Loikith, and M. Boustani, 2013: Evaluation of the surface air temperature, precipitation, and insolation over the conterminous U.S. in the NARCCAP multi-RCM hindcast using RCMES. *J. Climate*, in press.
- Whitehall, K., C. Mattmann, D. Waliser, J. Kim, C. Goodale, A. Hart, P. Ramirez, P. Zimdars, D. Crichton, G. Jenkins, C. Jones, G. Asrar, and B. Hewitson, 2012: Building model evaluation and decision support capacity for CORDEX. WMO Bulletin, 61, 29-34.

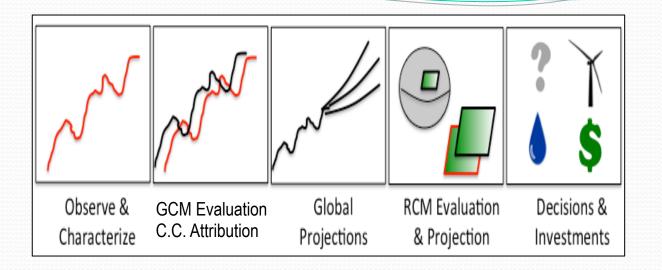
Climate change and impact assessments

- With the confirmation of global climate change of anthropogenic origins, assessing the impact of climate change on regional sectors has become an important concern.
- Climate change impact assessment is based on nested modeling in which information, and thus model errors, flows along the model hierarchy.



- Every climate model data contain biases due to *incomplete model formulations* as well as *imperfect external forcing information* (e.g., future GHG concentrations)
- To deal with model errors in climate projection and impact assessments, we usually rely on bias correction or multi-model ensemble, or both.
- Model evaluation is the key step in bias correction and multi-model ensemble.
- Systematic evaluations of GCMs have been undertaken for some time (e.g., AMIP, CMIP); this is not the case for RCMs.

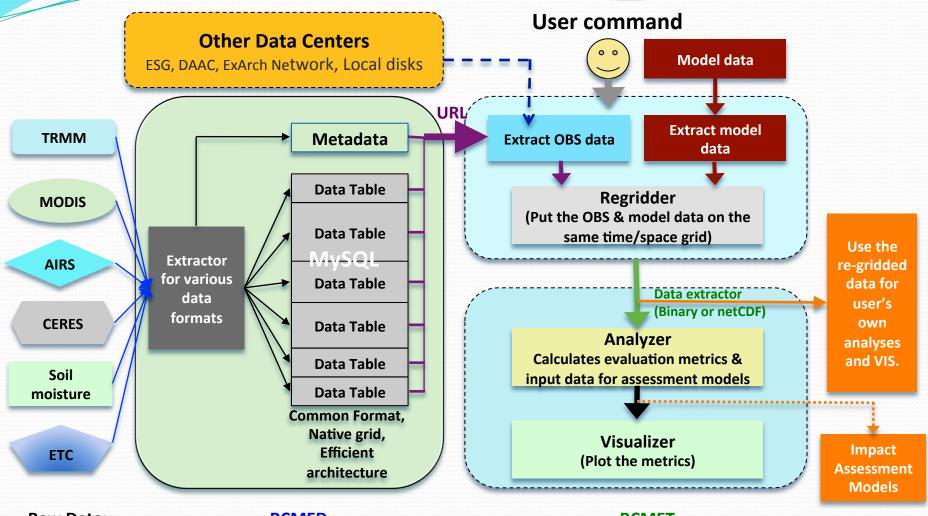
Observational Data in Climate Research and Modeling



- Observational data are a key in climate study & model development.
 - Detection of climate change signals and attribution of them
 - Model evaluation.
 - Easy access to high quality observational data facilitates evaluation efforts.
 - Remote-sensing at NASA & other institutions can provide fine-scale reference data suitable for evaluating (future) fine-resolution model simulations.
- To facilitate RCM evaluation, especially for easy access to remote sensing data, RCMES has been developed via joint JPL-UCLA efforts.

Regional Climate Model Evaluation System (RCMES version 2.1)

(http://rcmes.jpl.nasa.gov)



Raw Data:

Various sources, formats, Resolutions, Coverage

RCMED

(Regional Climate Model Evaluation Database)
A large scalable database to store data from variety
of sources in a common format

RCMET

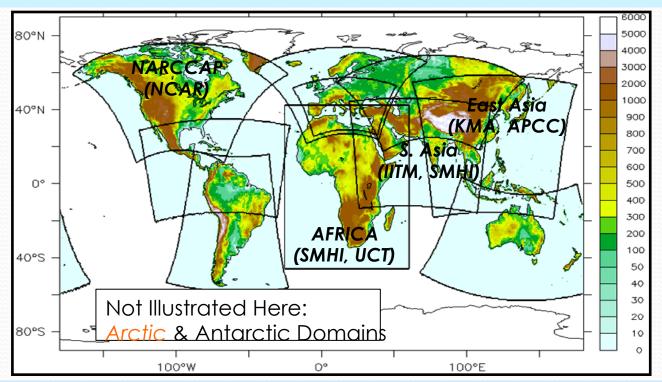
(Regional Climate Model Evaluation Tool)
A library of codes for extracting data from RCMED and model and for calculating evaluation metrics

USERS

User-specific software for flexibility

Ongoing and near-term applications of RCMES to the CORDEX Regions

- N. America: Funded via NASA for U.S. NCA (NCAR)
- Africa: Collaboration & analysis ongoing (UCT, SMHI)
- E. Asia: Available RCM data have been downloaded (KMA, APCC)
 - South Asia: Ongoing (IITM, SMHI)
 - Australia: Ongoing (Univ. of New South Wales)
- Arctic, Middle-East North Africa, Central America, South America: Planning stage



- Multi-RCM evaluation studies have been performed for two CORDEX domains, Africa and North America (NARCCAP)
 - CORDEX-Africa: 10-11 RCMs, 20 years (1989-2008)
 - NARCCAP: 5 6 RCMs,24-year (1980-2003).

Multi-RCM Evaluations using RCMES

- RCM biases in the Africa and North America regions are examined using the data from the multi-RCM CORDEX hindcast experiments.
- RCMES has been utilized to evaluate multi-RCM hindcast data for the two CORDEX domains.
- Monthly-mean hindcast data from multiple RCMs have been obtain from partnering institutions.
 - CORDEX-Africa: SMHI, 10-11 RCMs for the 20 years (1989-2008)
 - NARCCAP: NCAR, 5 6 RCMs for the 24-year (1980-2003).
 - All RCM data have been pre-interpolated onto a common analysis domain by the partnering institutions (SMHI and NCAR for the Africa and N. America, respectively) before transferred to the RCMES team.
- Evaluations have been performed for the variables that play crucial roles in shaping the surface climate
 - Precipitation, the daily surface air temperatures, cloudiness, insolation

CORDEX-Africa RCMs and the Analysis Domain

 All RCM data have been pre-interpolated from their native grid nests onto a regularly spaced at 0.44 degree horizontal resolutions for evaluation and analysis

Cloudiness

Χ

Χ

Χ

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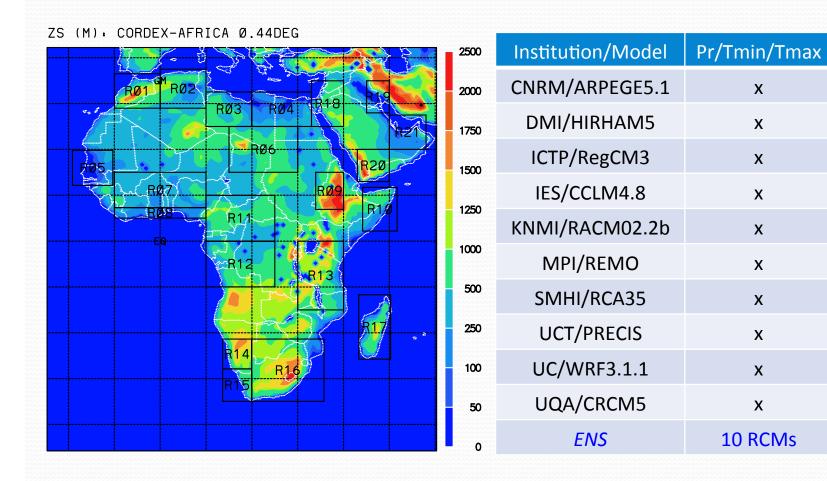
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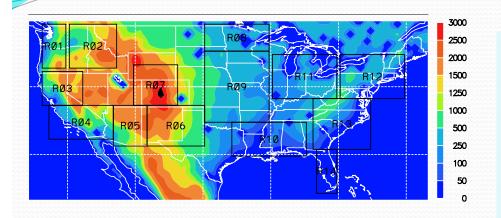
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9 RCMs

21 subregions are introduced to examine RCM skill in varied geography

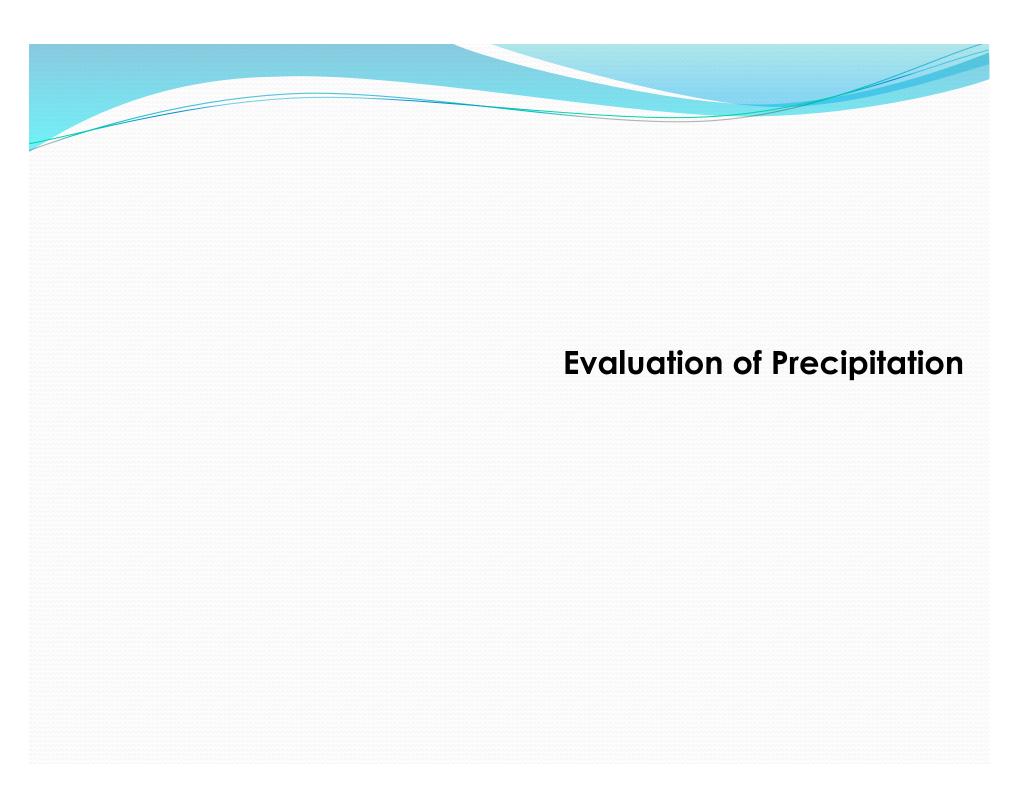


NARCCAP RCMs and the Analysis Domain

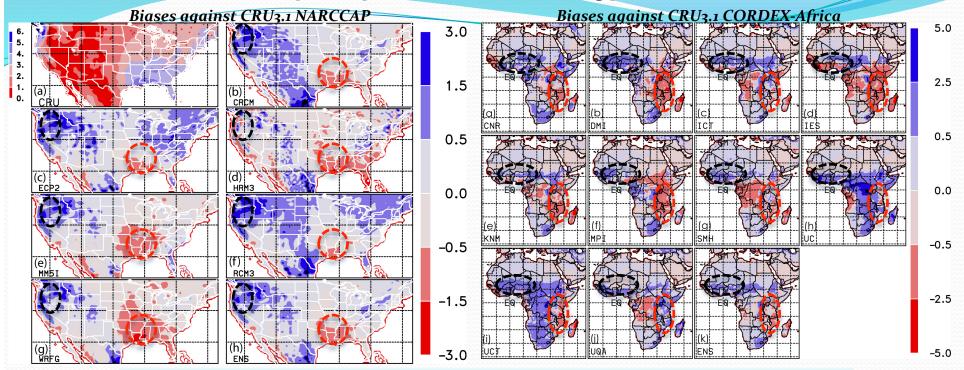


Model ID	Model Name
CRCM	Canadian RCM
ECP2	NCEP Regional Spectral Model
HRM3	Hadley Center RCM3
MM5I	MM5
RCM3	RegCM version3
WRFG	WRF – run at PNNL
ENS	Multi-model Ensemble

- The data from 5 RCMs and their ENS over the conterminous US region are evaluated.
- The RCM simulations have been preinterpolated from their native grids onto a common grid nest of 0.5-degree horizontal resolution by the NCAR team for analysis, evaluation, and intercomparison like in the CORDEX-Africa.
- Fourteen sub-regions (as shown in the figures and table) are selected to examine model performances in various regions of interests.

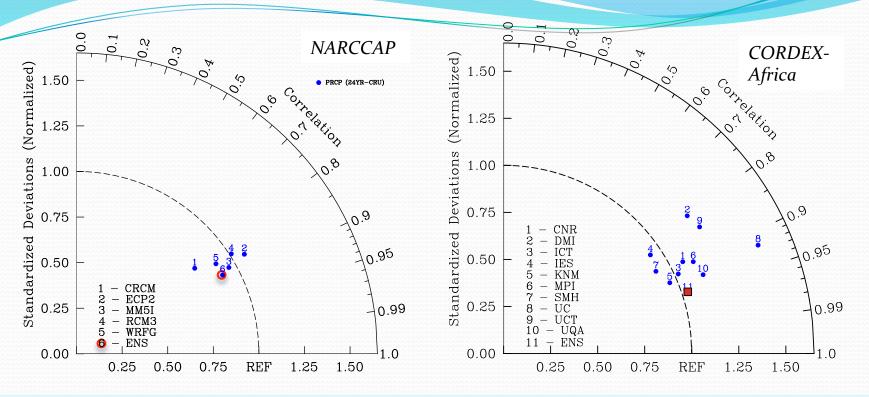


Annual precipitation Climatology and Biases



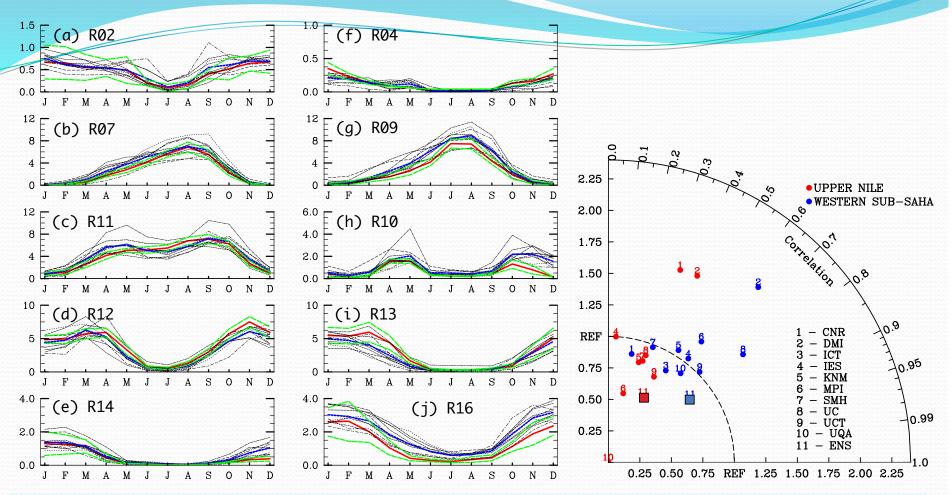
- Large inter-model variations in some regions:
 - SWUS, East Coast (US); the W. Tropics, W. Sahara (AF)
- There also exist systematic regional variations (see circles).
 - For the NARCCAP domain:
 - Wet biases in the Pacific NW
 - Dry biases in the Gulf coast and southern Great Plains.
 - For the Africa domain:
 - Wet biases in the Sahel region, South Africa
 - Dry biases in the E. Africa and E. Arabia Peninsula

Annual-mean Precipitation: Spatial Variability over the Land Surface



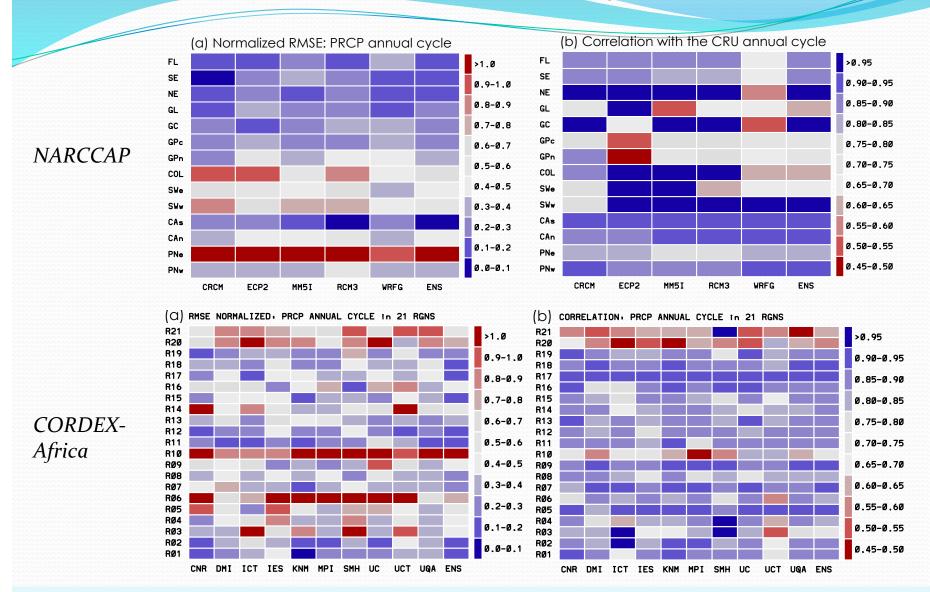
- All models show more similar performance in simulating spatial patterns; but, the magnitude of spatial variability (Standardized Deviations) varies more widely among models than the pattern correlation, especially for US.
- The multi-model ensemble (ENS) yields smaller RMSE than individual models included in the multi-model ensemble for both models.
- The multi-model ensemble tends to underestimate the magnitude of variability.

Precipitation annual cycle - Regional variations



- Model performance in simulating the precipitation annual cycle also varies according to regions for both the Africa (above) and NARCCAP (not shown) regions. For Africa,
 - All RCMs simulate the observed annual cycle reasonably well, at least its phase.
 - RCMs generally perform better for the western Africa than the eastern Africa.
 - The interannual variability of wet season rainfall is also better simulated for the western Sahel than the Ethiopian Highlands.

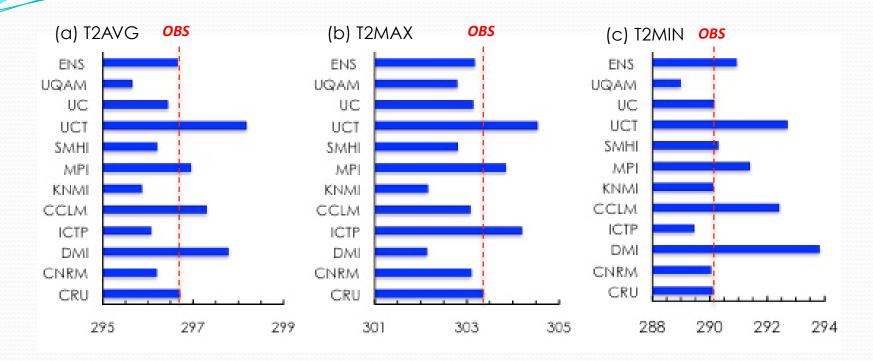
Precipitation Seasonal Cycle – Regional Summary



- Model performance in simulating the seasonal cycle show strong regional variations
- Model biases also vary for different metrics (RMSE & Correlation in the above)

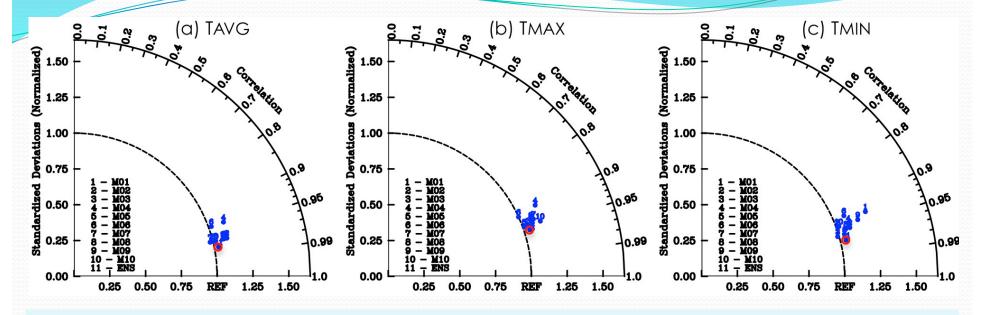
Annual-mean Surface Air Temperature Evaluation in the CORDEX-Africa Experiments

Annual-mean Surface Temperatures over the Land



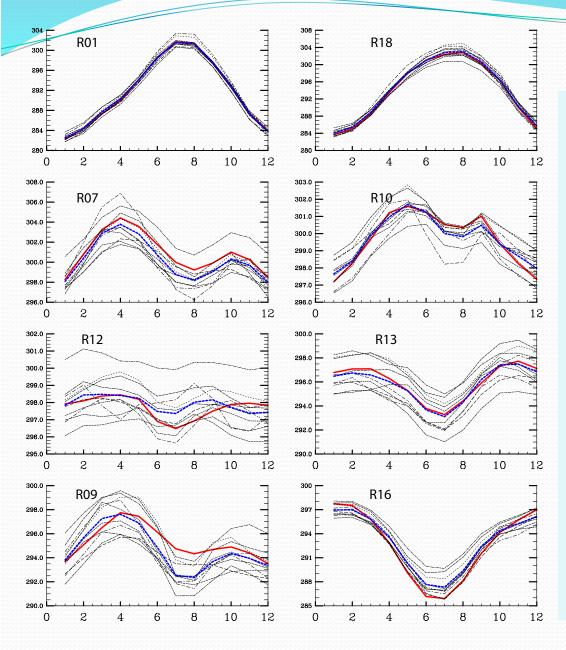
- Three surface air temperatures, the daily mean $(T2_{AVG})$, maximum $(T2_{MAX})$, and minimum $(T2_{MIN})$, are evaluated against the CRU3.1 data.
- All RCMs well simulate the land-mean $T2_{AVG}$ & $T2_{MAX}$, but most models overestimate $T2_{MIN}$.
- For $T2_{AVG}$ & $T2_{MAX}$, the multi-model ensemble (ENS) shows the best performance.

Annual-mean Temperatures: Spatial Variability over the Land



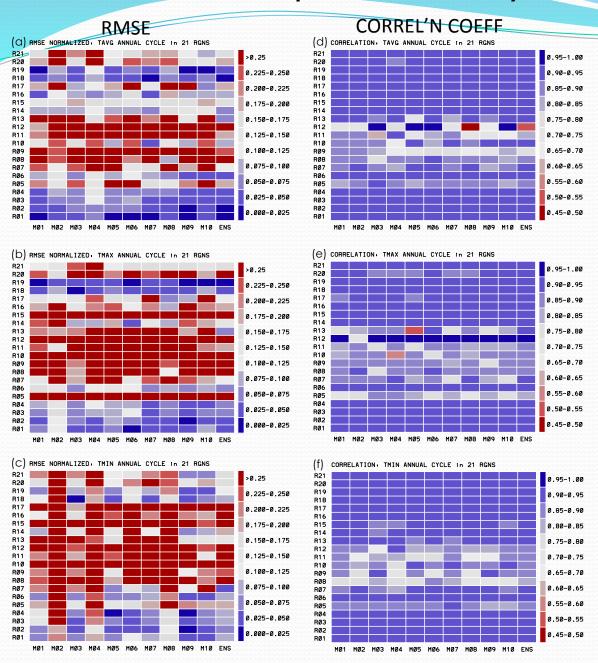
- All RCMs well simulate the spatial variability of the three surface temperatures.
- T_{AVG} shows the highest pattern correlation (0.9-0.98) with CRU among the three temperatures.
- the other two temperatures show smaller but comparable correlations.
- All RCMs perform similarly in simulating the magnitude of the spatial variability for T_{AVG} and T_{MAX} , but their performance varies widely for T_{MIN} .
- For all three temperatures, the multi-model Ensemble (ENS) yields the smallest RMSE similarly as for precipitation.

Precipitation annual cycle - Regional variations



- Model performance in simulating the daily-mean temperature annual cycle also varies according to regions for both the Africa (above) and NARCCAP (not shown) regions.
- For Africa, all RCMs perform better for the extratropical regions (e.g., Mediterranean coast, South Africa) than the inter-tropical regions (R09 & R12).
- Although multi-model ensemble agrees reasonably with the CRU data, inter-model variations in the simulated annual cycle increases close to the Equator.

Temperature Annual Cycle Evaluation



- Model performance in simulating the annual cycle show strong regional variations.
- Considering both RMSE and Correlation Coefficient, models generally perform better for simulating the annual cycle in the extratropics than in the tropics.
- Model biases also vary for different metrics.
- Similarly as for the overland variability, models generally perform better for $T_{\rm AVG}$ & $T_{\rm MAX}$ than $T_{\rm MIN}$.

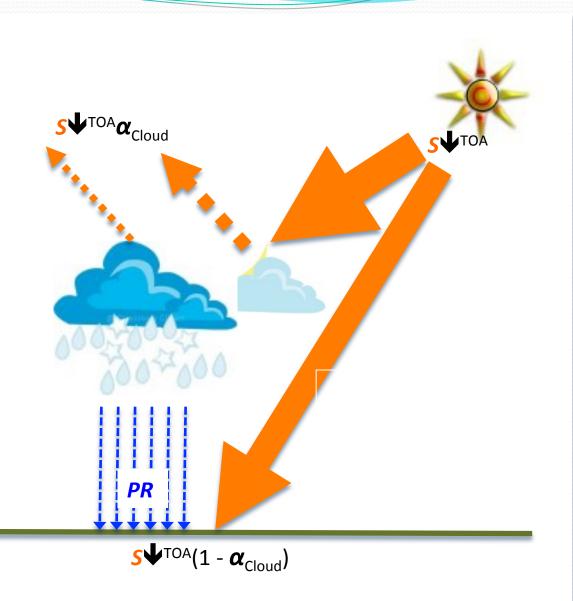
Relationships between the model biases in precipitation, cloudiness and surface insolation

Can this provide a clue for deficiencies in model formulations?

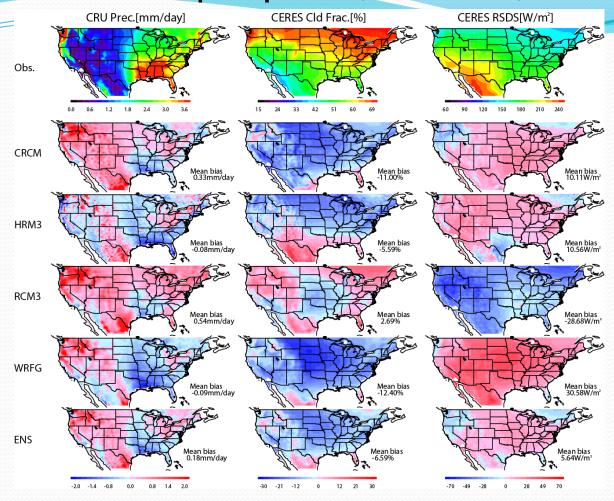
Precipitation, Surface Insolation, and Clouds

A simple schematic relationship

- Precipitation and surface insolation are related via clouds.
- Calculations of these three fields are among the most uncertain components in today's climate models.
- From above, it is expected:
 - Precipitation biases are positively correlated with cloudiness biases,
 - Surface insolation biases are negatively correlated with precipitation and cloudiness biases.
- Examine this hypothesis in the NARCCAP experiment.



Biases in Annual-mean precipitation, Cloudiness, and Insolation



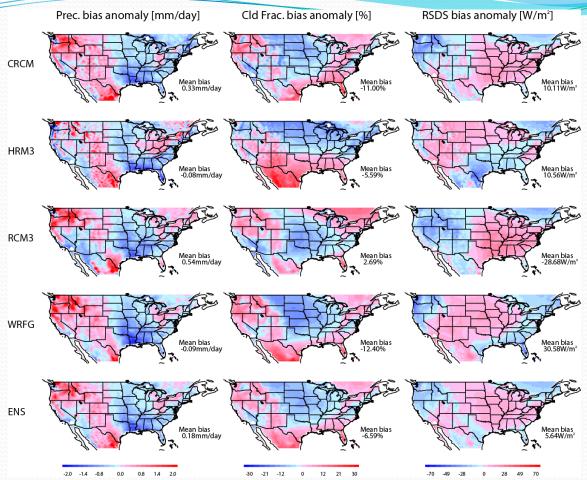
- Model biases show regionally systematic variations. E.g.,
 - Wet/Dry biases in the western US/Gulf of Mexico
 - Overall negative cloudiness biases in the US (Less –'ve or +'ve biases in WUS)
 - General +'ve biases in insolation except in the Pacific NW (Less -'ve or +'ve biases in EUS/Gulf of Mexico)
- The relationship between the three bias fields are not clear.

Biases in Precipitation, Cloudiness, and Insolation

	Model	PR (mm/day)	Cloudiness (%)	Insolation (W/m2)
All Year	CRCM	0.33	-11.0	10.1
	HRM3	-0.08	-5.6	10.6
	RCM3	-0.54	2.7	-28.7
	WRFG	-0.09	-12.4	30.6
	ENS	0.18	-6.6	5.6
Spring	CRCM	0.60	-12.8	10.7
	HRM3	0.22	-5.7	-43.5
	RCM3	0.96	5.5	-26.7
	WRFG	0.23	-12.9	35.6
	ENS	0.50	6.5	-6.0
Summer	CRCM	0.45	-11.7	29.9
	HRM3	-0.18	-7.9	31.0
	RCM3	0.62	-7.4	-28.1
	WRFG	-0.44	-16.9	49.6
	ENS	0.11	-11.0	20.6
Fall	CRCM	-0.04	-6.9	3.9
	HRM3	-0.51	-3.9	66.6
	RCM3	0.01	3.1	-32.9
	WRFG	-0.34	-11.9	23.5
	ENS	-0.22	-5.1	15.2
	CRCM	0.32	-12.6	-3.8
er	HRM3	0.16	-5.1	-11.6
Winter	RCM3	0.57	8.8	-27.0
	WRFG	0.16	-8.0	14.3
	ENS	0.31	-4.3	-7.0

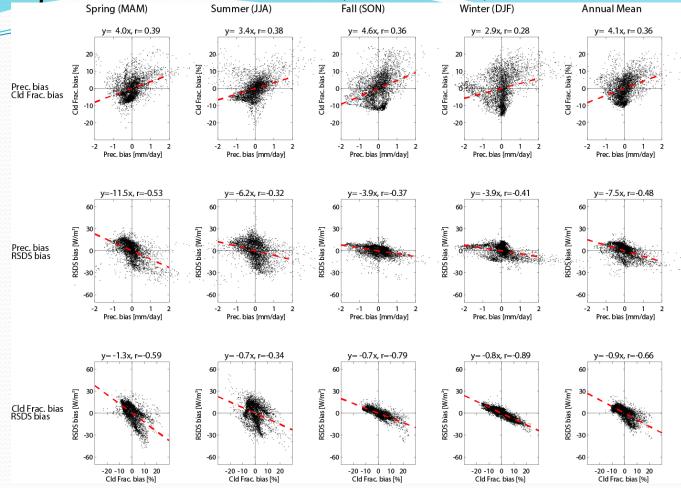
 The expected relationship between the biases in precipitation, cloudiness, and insolation does not exist for the land-mean biases.

Biases in Annual-mean precipitation, Cloudiness, and Insolation Spatial Anomalies



- Spatial anomalies of model biases show noticeable patterns
 - Most RCMS show positive/negative precipitation bias anomalies in WUS/EUS, most notably in the Pacific NW/Gulf of Mexico-Atlantic coast regions.
 - Insolation bias anomalies matches with those in precipitation (opposite signs).
 - Cloudiness bias anomalies are similar to those in precipitation (same signs).

Relationship between the biases in Pr, Cloudiness, and Insolation for the ENS



- The bias anomalies of multi-model ensemble shows consistent relationship between precipitation, insolation, and cloudiness for season totals as well as annual totals.
 - Positive correlation: PR vs. Cloudiness
 - Negative correlation: PR vs. Insolation & Cloudiness vs. Insolation
- The strongest correlation between cloudiness and surface insolation; the weakest for precipitation and cloudiness.

Biases in Precipitation, Cloudiness, and Insolation

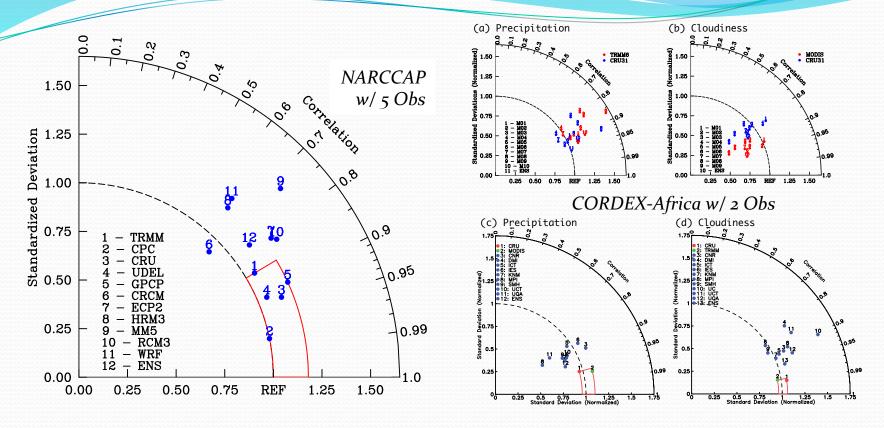
	Model	PR vs.	PR vs.	Cloudiness vs.
		Cloudiness	Insolation	Insolation
All Year	CRCM	0.24	-0.48	-0.46
	HRM3	0.29	-0.30	-0.51
	RCM3	0.47	-0.49	-0.64
	WRFG	0.36	-0.22	-0.60
	ENS	0.36	-0.48	-0.66
Spring	CRCM	0.30	-0.43	-0.45
	HRM3	0.36	-0.43	-0.49
	RCM3	0.59	-0.52	-0.75
	WRFG	0.39	-0.26	-0.75
Fall Summer	ENS	0.39	-0.53	-0.59
	CRCM	0.42	-0.35	-0.58
	HRM3	0.00	-0.33	0.03
	RCM3	0.59	-0.07	-0.22
	WRFG	0.22	-0.14	-0.56
	ENS	0.38	-0.32	-0.34
	CRCM	-0.06	-0.34	-0.50
	HRM3	0.40	-0.36	-0.58
	RCM3	0.53	-0.61	-0.57
	WRFG	0.40	-0.40	-0.44
	ENS	0.36	-0.37	-0.79
Winter	CRCM	0.08	-0.28	-0.72
	HRM3	0.27	-0.35	-0.75
	RCM3	0.37	-0.49	-0.82
	WRFG	0.38	-0.41	-0.79
	ENS	0.28	-0.41	-0.89

 The relationship between the spatial anomalies of model biases in PR, Cloudiness, and Insolation are consistent for nearly all models and seasons.

Uncertainties due to the Choice of the Reference Dataset(s)

- All reference datasets, typically from observations and assimilations, contain their own errors.
- Errors in the reference datasets are typically not well quantified.
- Uncertainty in reference data against which model results are compared can alter model evaluation results.

Evaluation of Spatial Variability using Multiple Reference Data



- Individual observations as well as models are 'evaluated' against the multiobservation ensemble.
- The evaluation metrics of multiple observation datasets vary noticeably although they are much smaller than those of models.
- Measured models can vary systematically according to the selection of reference data as shown for the cloudiness in the CORDEX-Africa domain.

Summary

- Evaluation of climate models is a fundamental step in model improvements as well as in projecting future climate and climate change impacts assessments.
- JPL/NASA is developing RCMES to facilitate climate model evaluation
 - A number of observed and remote sensing data have been collected
- Evaluation of the RCM data in the two independent regional climate hindcast experiments for Africa and North America shows that model errors vary systematically according to regions, seasons, variables, and metrics in addition to models.
- The multi-model ensemble is typically among the best performer in all evaluations.
- Relationship between the biases in related model variables may be useful in diagnosing model parameterizations of related processes.
- Evaluation results can vary, often substantially, according to the selection of the reference data.